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TEXTURE CLASSIFICATIONBY LOCAL BINARY PATTERN& COMPLETED LOCAL BINARY PATTERN

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ABSTRACT

Texture analysis is important in many applications of computer image analysis for classification or segmentation of images based on local spatial variations of intensity or color. The proposed analysis of texture classification characteristics with local binary pattern (LBP) and an associated completed LBP (CLBP).A successful classification or segmentation requires an efficient description of image texture. In this system, image features of database images will be extracted using LBP & CLBP descriptor. These extracted features in the form of histogram will be given to SVM classifier and depending on no. of accurately classified images; results will be shown in graph.

KEYWORDS: Texture descriptors, local binary pattern (LBP), feature extraction, texture classification.

Introduction:

Texture is a fundamental characteristic of the appearance of virtually all natural surfaces and is ubiquitous in natural images. Being the major problems in texture analysis, considerable attention is given to texture classification during the past decades, due to its value both in understanding how the texture recognition process works in humans as well as in the important role it plays in the field of computer vision and pattern recognition. Typical applications of texture classification are medical image analysis and understanding, object recognition, content-based image retrieval, remote sensing, industrial inspection, and document classification.

Among local texture descriptors, Local Binary Pattern (LBP) [1] has emerged as one of the most prominent and has attracted increasing attention in the field of image processing and computer vision due to its outstanding advantages. Ease of implementation, no need for pre-training and low computational complexity makes LBP a preferred choice for many applications.Although originally proposed for texture analysis, the LBP method has been successfully applied to many diverse areas of image processing such as dynamic texture recognition, remote sensing, fingerprint matching, visual inspection, image retrieval, biomedical image analysis, face image analysis, motion analysis, edge detection, and environment modeling [5].

Completed LBP (CLBP) is with improved rotation invariance, lower dimensionality & satisfactory discriminative power. Along with the original LBP, CLBP approach combines the information on center pixel, signed differences & magnitude of differences.Texture analysis is important in many applications of computer image analysis for classification or segmentation of images based on local spatial variations of intensity or color.A successful classification or segmentation requires an efficient description of image texture. Important applications include industrial and biomedical surface inspection, for example for defects and disease, ground classification and segmentation of satellite or aerial imagery, segmentation of textured regions in document analysis, and content-based access to image databases.

Materials and Methods:

Li Liu, Yunli Long, Paul W. Fieguth [2014]

In this paper, they have proposed a simple, efficient, yet robust multi-resolution approach to texture classification—binary rotation invariant and noise tolerant (BRINT).The proposed approach is very fast to build, very compact while remaining robust to illumination variations, rotation changes, and noise. A local binary descriptor based on the conventional local binary pattern (LBP) approach, preserves the advantageous characteristics of uniform LBP. Points are sampled in a circular neighborhood, with number of bins in a single-scale LBP histogram constant and small, so arbitrarily large circular neighborhood scan be sampled and compactly encoded over a number of scales.

Li Liu and Paul W. Fieguth et al. [2012]

This paper presents a simple, very powerful approach for texture classification based on random projection, suitable for large texture database applications. At the feature extraction stage, a small set of random features is extracted from local image patches. Learning and classification are carried out in a compressed domain. Extensive experiments show that on each of the CUReT, the Brodatz, and the MSRC databases. This paper shows that this approach leads to significant improvements in classification accuracy and reductions in feature dimensionality.

Fakhry M. Khellah et al. [2011]

Texture features are obtained by generating an estimated global map, which represents the measured intensity similarity between any given image pixel and its surrounding neighbors within a certain window.The intensity similarity map is an average representation of the texture-image dominant neighborhood similarity. The estimated dominant neighborhood similarity is robust to noise and referred to as image dominant neighborhood structure.The global rotation-invariant features are then extracted from the generated image dominant neighborhood structure. Features obtained from the local binary patterns (LBPs) are then extracted in order to supply additional local texture features to the generated features from the dominant neighborhood structure.

ManikVarma ,AndrewZisserman et al. [2009]

In this paper, investigation of material classification from single images obtained under unknown viewpoint and illumination is obtained.It is demonstrated that materials can be classified using the joint distribution of intensity values over extremely compact neighborhoods. The performance of filter banks is inferior to that of image patches with equivalent neighborhoods.They have developed novel texton based representations which are suited to modeling this joint neighborhood distribution for Markov random fields. Three such representations are proposed and their performance is assessed and compared to that of filter banks.

TimoOjala, MattiPietikaÈinen et al.[2002]

This paper presents a theoretically very simple, yet efficient, multi-resolution approach to gray-scale and rotation invariant texture classification based on local binary patterns. The method is based on recognizing that certain local binary patterns, termed uniform are fundamental properties of local image texture and their occurrence histogram is proven to be a very powerful texture feature.Excellent experimental results obtained in true problems of rotation invariance, where the classifier is trained at one particular rotation angle and tested with samples from other rotation angles; demonstrate that good discrimination can be achieved with the occurrence statistics of simple rotation invariant local binary patterns.

B.S. Manjunath and W.Y. Ma et al. [1996]

The focus of this paper is on the image processing aspects and in particular using texture information for browsing and retrieval of large image data.They have proposed the use of Gabor wavelet features for texture analysis and provide a comprehensive experimental evaluation. From these many research papers it is concluded that despite the limitations, the original LBP has been modified to its variants depending on applications.

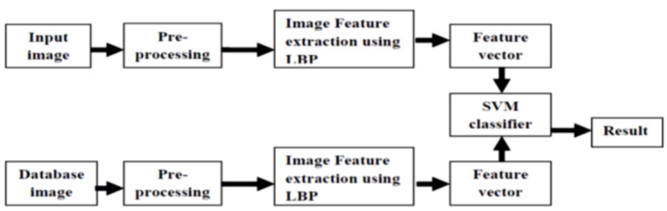

Fig.1.Image feature extraction using LBP

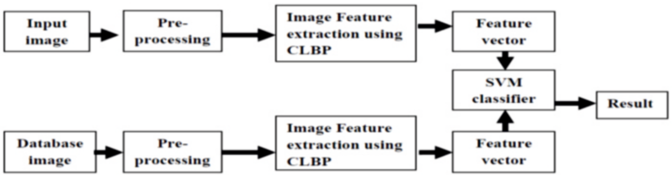

Fig.2.Image feature extraction using CLBP

Local Binary Pattern (LBP)

Local Binary Pattern (LBP) is most popular due to its computational simplicity and good performance. The original LBP method, characterizes the spatial structure of a local image texture by thresholding neighborhood with the value of the center pixel and considering only the sign information to form a local binary pattern. In the original LBP method, a local image texture is thresholded in a 3 × 3 square neighborhood with the value of the center pixel (xc) and considering only the sign information to form a local binary pattern.Given a pixel xcin the image, the LBP pattern is computed by comparing itsvalue with those of its p neighboring pixelswhich are evenly distributed in an angle with radius r.

$$x_{r,p} = [x_{r,p,0,......,}xr,p,p-1]^T$$

the LBP operator takes the following form:

$$\sum_{n=0}^{p-1} s(x_{r,p,n} - x_c)2^n \ , \ s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

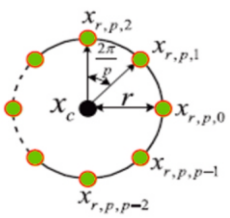

Fig.3 The(r, p) neighborhood type used to derive a LBP like operator central pixel and its p circularly and evenly spaced neighbors on circle of radius r.

Completed Local Binary Pattern (CLBP)

Completed Local Binary Patterns (CLBP) consist of three LBP-like descriptors: CLBP_C, CLBP_S and CLBP_M which include information on the center pixel, signed differences, and magnitudes of differences, respectively, with the variants tested to improve the discriminative power of the original LBP operator.The CLBP_S descriptor is same as the original LBP descriptor; CLBP_C thresholds the central pixel against the global means gray value of the whole image. CLBP_M performs a binary comparison between the absolute value of the difference between the central pixel and its neighbors and a global threshold to generate an LBP-like code.The sign component preserves the information of local difference. The magnitude component contributes additional discriminant information. Also, the intensity value of the center pixel itself can also contribute useful information.The original image is presented as its center gray level (C) and the local difference. So,CLBP_C, CLBP_S and CLBP_M, can be coded the C, S, and M features, respectively.

The CLBP_C, CLBP_S, and CLBP_M codes together form the CLBP feature map of the original image. A CLBP histogram can be built, and some classifier as Support Vector Machinecan be used for texture classification. The CLBP_S operator is the same as the original LBP operator. Instead of the binary 1 and -1 values, the M components are of continuous values and they cannot be directly coded as that of S. we define the following CLBP_M operator as:

$$CLBP\_M_{P,R} = \sum_{p=0}^{P-1} t(mp,c)2$$

Wherec is a threshold that is to be determined adaptively. We set it as the mean value of mp from the whole image. Both CLBP_S and CLBP_M produce binary strings so as to use themconveniently together for pattern classification.

The center pixel, which expresses the image local gray level, also has discriminant information. To make it consistent with CLBP_S and CLBP_M, we code it as,

$$CLBP\_C_{P,R} = t(gc, c_1)$$

Where c1 is set as the average gray level of the whole image. The three operators, CLBP_S, CLBP_M, and CLBP_C, could be combined in two ways, jointly or hybrid.

In the first way, similar to the 2-D joint histogram, we can build a 3-D joint histogram of them, demoted by "CLBP_S/M/C". In the second way, a 2-D joint histogram, "CLBP_S/C" or "CLBP_M/C" is built first, and then the histogram is converted to a 1Dhistogram, which is then concatenated with CLBP_M or CLBP_S to generate a joint histogram, denoted by "CLBP_M_S/C" or "CLBP_S_M/C".

Support Vector Machine (SVM):

SVM maps input vectors to a higher dimensional vector space where an optimal hyper plane is constructed. Among the many hyper planes available, there is only one hyper plane that maximizes the distance between itself and the nearest data vectors of each category. This hyper plane which maximizes the margin is called the optimal separating hyper-plane and the margin is defined as the sum of distances of the hyper-plane to the closest training vectors of each category. This used to separate the class of set.

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